Personal Visualisation for Learning

Roberts, Jonathan C.; Headleand, Christopher; Perkins, Dave; Ritsos, Panagiotis D.

Published: 01/01/2015

Peer reviewed version

Cyswllt i'r cyhoeddiad / Link to publication

Dyfyniad o'r fersiwn a gyhoeddwyd / Citation for published version (APA):
Roberts, J. C., Headleand, C., Perkins, D., & Ritsos, P. D. (2015). *Personal Visualisation for Learning*. 4. Paper presented at Personal Visualization: Exploring Data in Everyday Life Workshop, IEEE Conference on Visualization (VIS), Chicago, IL, USA, Chicago, United States.

Personal Visualization for Learning

Jonathan C. Roberts*
Bangor University, UK

Christopher Headleand†
Bangor University, UK

David Perkins‡
Bangor University, UK

Panagiotis D. Ritsos§
University of Chester, UK

ABSTRACT

Learners have personal data, such as grades, feedback and statistics on how they fair or compare with the class. But, data focusing on their personal learning is lacking, as it does not get updated regularly (being updated at the end of a taught session) and the displayed information is generally a single grade. Consequently, it is difficult for students to use this information to adapt their behavior, and help them on their learning journey. Yet, there is a rich set of data that could be captured and help students learn better. What is required is dynamically, regularly updated personal data, that is displayed to students in a timely way. Such 'personal data' can be presented to the student through 'personal visualizations' that engender 'personal learning'. In this paper we discuss our journey into developing learning systems and our resulting experience with learners. We present a vision, to integrate new technologies and visualization solutions, in order to encourage and develop personal learning that employs the visualization of personal learning data.

Keywords: Learning Analytics, Personal Learning, Personal Data, Information Visualization, Teaching Analytics, Learning Support

Index Terms: K.6.1 [Management of Computing and Information Systems]: Project and People Management—Life Cycle; K.7.m [The Computing Profession]: Miscellaneous—Ethics

1 INTRODUCTION

In the Higher Education sector (especially) the concept of *Personal Learning* (PL) is gaining momentum. Within this agenda, academics are moving from *content-based learning* to *student-centric learning*, where an individual assumes responsibility for setting their own goals. While there is much rhetoric around these ideas and there are many practical ways to achieve this shift in focus, the overarching ideology is a good one: to empower the students with resources that enable them to learn better, based on their own data. Ken Robinson encourages students to find 'their element' [20], to find their own path and develop an innate love and genuine interest for their subject. This *learner empowerment* matches deep learning with research integration and *futures thinking* [22]. This is a two-way journey of a learner understanding themself *personally*, their emotions, moods and sensations, and *externally* of the material world, events and circumstances.

So, how can we encourage and empower learners to become more conscious of their learning? How can we deepen learner's understanding of what they have learnt? How can they adapt learning strategies to their own skill-set and style or see how well they are doing in comparison to others? How can they plan, manage and qualify their learning? How do we capture data – and what data – to help learners realize how they are progressing? How can we assist students using visualizations that effectively depict their progress, learning context and results?

*e-mail: j.c.roberts@bangor.ac.uk
†e-mail:c.headleand@bangor.ac.uk
‡e-mail:d.perkins@bangor.ac.uk
§e-mail:p.ritsos@chester.ac.uk

Our position is that *personal visualization* and especially *personal visual analytics* can help tackle these questions. Our focus and thoughts are born from our experiences within Higher Education, but we believe that the principles and ideas can be applied to a broader range of educational activities.

We organise the paper in four parts: (1) provide background that gives context to the personal data for learning; (2) highlight core related work; (3) focus on our experience and explain some key projects that we have been involved with, and (4) develop a vision for personal learning visualization. The aim is to motivate and excite the community to develop further the concept of *personal data visualization* for learning (Fig. 1).

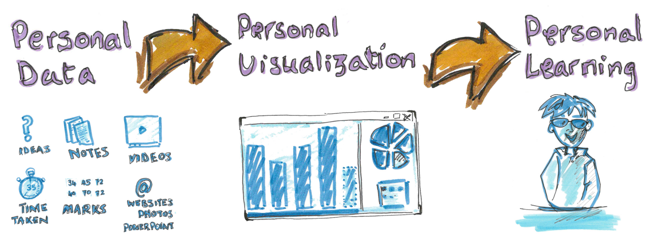

Figure 1: From personal data, personal visualization to personal learning.

2 BACKGROUND & CONTEXT

There are many kinds of student data that a University currently stores. These include: address, qualifications, degree major, modules or units of work to be achieved and grades. Students can view (and edit) some of this information via a 'student portal' and access learning resources through systems such as Moodle or Blackboard. These Learning Management Systems (LMS) provide students with access to individual grades, lecture materials, assessments and other resources the learner might require. Usually, the instructor has access to a more detailed overview of all students' performance. It is likely, however, that grade information is stored in many places and students have to use several 'portals' (e.g., term-time assessment results may be stored on a separate portal to overall grades).

These systems provide a personal view, where an individual student only sees his/her grades. It is also true that these portals are becoming more feature rich and are starting to depict students grades visually. In fact, Universities are endeavoring to make the learning experience more personal, for instance:

- Strategies such as Personal Learning Plans (PLPs) are gaining popularity where students set their own goals, monitor their own progress and identify their own aims.
- Personal Learning Records (PLRs) are being introduced, where the students not only get a transcript of their grades but also receive a fully detailed document of all their subjects, learning outcomes, and extracurricular activities.
- Students are gaining more authority over their own data, and can record their own personal notes, which their tutor would receive.

However, there are several challenges with current systems. They do not capture detailed information about the student (especially information that may help them realize their own mistakes). The data granularity is poor, and only updates at major events (e.g., assessment milestones and examination results). Metadata such as notes by the student, academic and tutor, cannot be stored alongside the results. Existing systems are often not integrated and students and administrators have to utilize many different – often incompatible – tools. In order to reach a point where we can realize personal learning visualization we need to address many of these challenges.

There are obviously many different kinds of personal data that could be captured and stored. As we discuss below, at our institutions we capture attendance data, student satisfaction, and per-module evaluation data. But, it is unclear what other personal data may be useful in helping learners. In fact, some data that may seem ideal to capture, may be subject to privacy and legality restrictions.

For inspiration, let's consider the field of exercise. Users have activity trackers like Fitbit or smartwatches (such as the Apple Watch), that capture personal data and display them through special services as daily or weekly reports of their progress. These services gamify the whole progress, by gauging how well users are doing in comparison with others. They indicate notable achievements or goals and offer digital 'rewards' (tags, badges etc.), that people can display on social networks, as encouragement and support. What is required for the learning domain is a similar approach: systems that automatically monitor progress, provide regular reports, and enable and encourage the student to do better.

3 Related Work

In the context of this paper, and with an outlook to visualization, we look into related work in two dimensions: i) personal data capture and ii) personal learning visualization.

3.1 Capturing personal data

Nowadays, *Educational Data Mining* (EDM) [21] and *Learning Analytics* (LA) [5] are converging. There is a shift from EDM merely informing educational practice to directly influencing it. LA is becoming a timely research topic and several researchers (including ourselves) make calls to the analytics communities to step up [4, 17]. Along with the enthusiasm of LA is the appetite for visualization (especially visual analytics). E.g., in 2015 the 'Learning Analytics and Knowledge' conference convenes its fifth event and holds its first workshop on Visual Approaches to Learning Analytics (visla15.org).

We already mentioned a growing interest in Personalized Learning Environments (PLEs), where a learner self-adapts their learning environment to suit their own particular learning needs [2]. We are also beginning to see data-driven systems personalized for the learner, such as recommender systems [8, 26] that help identify items such as learning resources and knowledge routes [9]. Powell and Yuan [29] argue that personal data can provide higher-level insights into how students learn. Nonetheless, while these data-driven insights are proving to be of benefit to educators, learners are often have limited access, constricting their possible reflections.

Looking at other domains, the tracking of personal data is becoming increasingly ubiquitous, helping individuals identify their habits and understand patterns in their behavior [24]. In recent years, with the advent of mobile and wearable [16] technology, and the Internet of Things [19], self tracking has become a disruptive innovation in an number of domains [25], including fitness [13] and sleep activity [7]. As these technologies become more and more pervasive, there are opportunities to employ them in educational context, in complementary fashion to traditional methods, and enrich the quality of captured data.

Figure 2: The IVY learning environemnt for language interpreters, showing a learning scene.

Figure 3: Picture from Technocamps, building Lego Mindstorm robots.

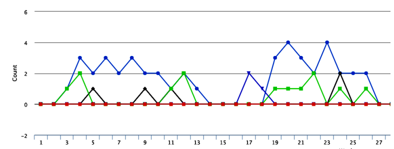

Figure 4: Attendance monitoring record of a typical student.

3.2 Personalizing Learning Visualizations

The continuous increase in learning data (produced and captured) presents several visualization opportunities, in order to allow a student to reflect on their progress [6], compare themselves with their peers [23], provide greater context to acquired skills [11] or to build and depict predictive models [12]. However, there has been little research into how these visualizations can be personalized, to support a students learning style and individual needs.

Systems such as CourseVis [10], Moodle (moodle.org), Blackboard (blackboard.com) etc. all display the information in dashboards resembling the style of Google Analytics. About half of the tools discussed by Verbet et al. [27] display time spent, social interaction and tool use. In some cases students can customize data representations through these dashboard systems [3] enabling a level of self-reflection and greater understanding of personal performance.

Yet, for users to explore any information, they need to load a separate dashboards, often isolated from the learning materials and specific results and metrics (e.g., exam vs. term-time assessments). There is an opportunity to do more than merely displaying dashboards of grades, by integrating personal data, students' learning goals, pathways and objectives.

4 Case Studies

To develop the direction of personal learning data, we look to our own experiences for guidance, and briefly discuss four projects.

The IVY project [15] (Fig. 2) was funded by the European Union, and was a collaboration between six EU partners. The aim was to create a collaborative environment (The IVY-Virtual Environment) to train language interpreters. Several scenarios were developed, where students could learn interpreter-mediated communication skills, through being immersed in a 3D virtual world. Data of scenario usage, timings, repetition of loading materials etc. is captured. In the follow-up project (EVIVA) data stored included videos, recorded by the users as they used IVY-VE.

Technocamps (Fig. 3) was a four year outreach project designed to inspire the young people of Wales to select more Science Technology Engineering and Maths (STEM) subjects at school, and to encourage more school leavers to take STEM-based degrees or other employment. Hundreds of workshops were organized, most focused on constructionist approaches (learning by doing), using tools such as Lego Mindstorms, Mindcraft, and computer programming in Scratch, Greenfoot, etc.

Five Desing Sheets (FdS) (fds.design) methodology, for lo-fidelity sketching and planning of visualization interfaces, has been developed and applied by the authors [18]. FdS has been used in summer schools, computer science third-year projects, and taught modules.

Student monitoring is a major challenge in Universities. In the UK there is a requirement by Border Agencies to monitor attendance of non-UK students. Using the OPN 2001 handheld barcode data collector we scan students' identity cards as they exit the lecture or class. This attendance data is then uploaded to a database and visualized in several ways. For instance, the information is displayed on each students' dashboard as a line plot (Fig. 4), and a visual summary of all students' attendance can be viewed in an administrator portal, for cohort monitoring.

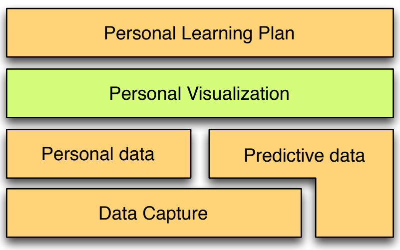

Figure 5: A tiered model, focusing on data capture, prediction, visualization. To allow students to develop Personal Learning Plans.

5 Vision for Personal Learning Visualization

Our vision is to i) place visualization at the heart of the learning environment (rather than an afterthought), ii) put the user in control of their own learning experience, and iii) use a wide range of data as input. We propose a tiered approach where most data is captured, some is predicted, then visualized and used by students to develop their personal learning plan (see Fig. 5).

Let's consider Steve, an imaginary second year student on a computer science major. He has a set of modules that he has completed in his first year. This gives him a credit score and also a grade point average. He looks at a visualization of how well he did in the previous year, and via an interface explores his activity in specific modules. He sees his notes and realizes that he put less time into certain modules. He then makes a comparison of his results to other students, (using a map-like visualization, Fig. 6). In the visualization, he can click on better students (depicted anonymously) and explore their grades and progression paths. He then turns his attention to next year.

Looking at a visualization of predicted results, he can see how his module grades could turn out. Through this information the system helps him create a Personal Learning Plan. The plan includes visualizations of his current grades, along with courses to help him improve on certain skills. Steve does not understand some statistical analysis that was used, and refers to expanded tool-tips providing additional information, including explanatory animations. The visualizations nudge Steve to register for several additional courses, which focus on key skills that he identified he is lacking.

But Steve would not use the system unless the data can be easily captured. Data gathering must be seamless and transparent with no extra effort. We have had first hand experience of this with our attendance monitoring. Originally paper-based monitoring was used. But academics saw it as a burden, and mistakes happened frequently. Nonetheless, with the scanner we are able to automate much of this process. The visualizations and the underpinning database help tutors and students see their record (and can make requests for correction should they be legitimately miss the class). It is important, therefore, that data capture is transparent and seamless, very much as dictated by ubiquitous computing [28].

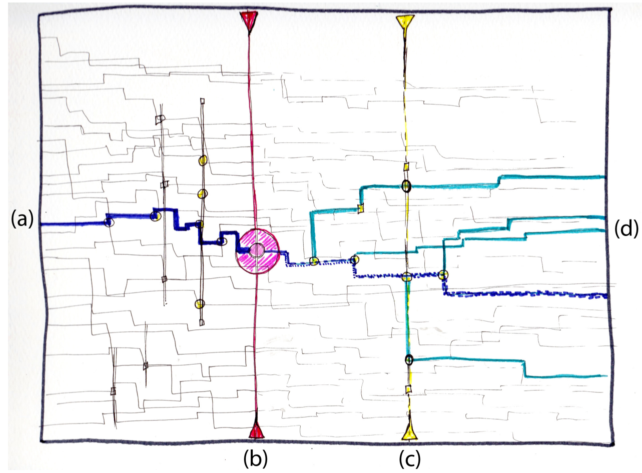

Figure 6: A sketch of a proposed students' journey. Red shows the current time, possible routes are depicted in cyan, and key moments are shown with circles.

There are certainly similarities between the gamification of the fitness world and our vision. Users can see their own exercise records, set goals and have competitions with their peers. This is a useful comparison because both domains have goals (get fitter, learn better) and both set targets (lose weight, improve marks). However, there are also major differences and potential pitfalls with this comparison. For instance, a significant factor is the time frame under which we observe change. Fitness has metrics that update on a minute or second scale and fairly short term goals, whereas education has (typically) longer term goals with longer term metrics. In addition, tracking mechanisms (e.g., wearables) for fitness may have matured, however similar educational monitors are less mature, and maybe (if they are intrusive) more controversial.

Another important consideration is the relative value of the information to the user and how it will impact on their lives. In 2013, Rackspace [14] published a model with six classifications of the way in which the user would regard wearable data. Over 80% of the 4000 respondents claimed that the wearable technology boosts their personal abilities. If a similar impact can be achieved within education there is an opportunity to make the collection and visualization of personal learning data have a profound influence in the domain.

Moreover, there is need to capture and visualize a wide range of data, e.g., student's or tutor's notes, observations, institution-related metrics such as attendance and National Student Survey (NSS) records, and grades of different types of assessment. In addition, HCI techniques [4] can be employed to track how students access educational content, how much time they spend studying it etc. Multimodal techniques (e.g., eye and gesture tracking, biosensors, etc.) could be used to devise more naturalistic assessments, giving insight to "overt and tacit" aspects that indicate a student's expertise on a subject [1].

Finally, the visualizations themselves need to have a profound impact. They should *nudge* or change student behavior in a positive way. They could act as suggestions or demonstrations of specific milestones within the learning journey. In fact, we imagine that the aforementioned visualization, using a map-metaphor, would act as an important reference. It would allow users to see their *learning journey*, how well they have done (compared to others), give suggestions over possible outcomes, and allow them to drill down into specific marks (see Fig. 6). This concept is inspired from the sketchbooks appearing in the Adjustment Bureau (2011) film. In our sketch, individual lines represent the progress of a student. Students' grades are shown as black lines, with time running on the x-axis. The y-axis represent an aggregated score of metrics (such as grades, time spent, notes taken etc.) Thus the flow of these lines can go up (generally doing better) and down (doing worse). The red line and circle show 'today', with the yellow bar for the next Semester and the cyan routes for grade predictions.

6 Conclusions

There is much research to be done to achieve our vision. Not only do we need easy ways to capture personal data, but data must be captured sensitively. There are three enabling factors that need to mature, to make personal learning a pervasive idea. Researchers need to:

- investigate good ways to capture and deliver personal data.
- develop personal visualizations, that are suitable for an individual and their needs, as well as the learning context.
- integrate personal planning and development strategies. Students need ways to plan and manage their learning, monitor their development, and take charge of their own learning progress.

In our particular case, students also have to see a clear benefit of these personal visualizations, such to persuade them to put extra effort into storing and manipulating personal data. There are also other potential challenges, where some students may feel that this is too much of an intrusion into their own personal life and activities. Consequently, data security and anonymization must be a priority.

New visualization techniques are required to display this information. The created designs must be understandable by users who may have little knowledge of specific visualization techniques. We also believe that the visualizations created need to be first-class-citizens, i.e., when these tools are created, developers should first think how the information is going to be displayed, and how a user is going to manipulate it. Too often the display of such data is an afterthought.

Personal visualization is a growing sub-area of visualization. While there are certainly many challenges ahead, there are also many benefits and opportunities. Personal learning is gaining momentum, and therefore we encourage researchers and academics to think how personal visualization can aid to achieve and enhance personal learning at whatever level of education, whether School, College or University.

References

[1] P. Blikstein. Multimodal learning analytics. In *Proc. Learning Analytics and Knowledge*, LAK '13, pages 102–106. ACM, 2013.

[2] M. A. Chatti, A. L. Dyckhoff, U. Schroeder, and H. Thüs. A reference model for learning analytics. *IJTEL*, 4(5-6):318–331, 2012.

[3] A. Cuttone, M. K. Petersen, and J. E. Larsen. Four data visualization heuristics to facilitate reflection in personal informatics. In *Universal Access in Human-Computer Interaction*, pages 541–552. Springer, 2014.

[4] A. Dix and J. Leavesley. Learning analytics for the academic: An action perspective. *J-UCS*, 21(1):48–65, jan 2015.

[5] R. Ferguson. Learning analytics: drivers, developments and challenges. *IJTEL*, 4(5-6):304–317, 2012.

[6] S. Govaerts, K. Verbert, J. Klerkx, and E. Duval. Visualizing activities for self-reflection and awareness. In *ICWL*, pages 91–100. Springer, 2010.

[7] M. Kay, E. K. Choe, J. Shepherd, B. Greenstein, N. Watson, S. Consolvo, and J. A. Kientz. Lullaby: a capture & access system for understanding the sleep environment. In *Proc. Ubiquitous Computing*, pages 226–234. ACM, 2012.

[8] N. Manouselis, H. Drachsler, R. Vuorikari, H. Hummel, and R. Koper. Recommender systems in technology enhanced learning. In *Recommender systems handbook*, pages 387–415. Springer, 2011.

[9] N. Manouselis and D. Sampson. Dynamic knowledge route selection for personalised learning environments using multiple criteria. In *Workshop on Intelligence and Technology in Educational Applications (ITEA2002)*, number 1, pages 448–453. IASTED, 2002.

[10] R. Mazza and V. Dimitrova. Coursevis: A graphical student monitoring tool for supporting instructors in web-based distance courses. *Int J Hum-comput st.*, 65(2):125 – 139, 2007.

[11] A. Nussbaumer. Supporting self-reflection through presenting visual feedback of adaptive assessment and self-evaluation tools. In *Proc. Interactive Computer-aided Learning (ICL 2008)*, pages 24–26, 2008.

[12] A. G. Picciano. The evolution of big data and learning analytics in american higher education. *J Asynchronous Learning Net.*, 16(3):9–20, 2012.

[13] S. Purpura, V. Schwanda, K. Williams, W. Stubler, and P. Sengers. Fit4life: the design of a persuasive technology promoting healthy behavior and ideal weight. In *Proc. SIGCHI Human Factors in Computing Systems*, pages 423–432. ACM, 2011.

[14] RackSpace. The human cloud: Wearable technology from novelty to production. Company Website, June 2013.

[15] P. D. Ritsos, R. Gittins, S. Braun, C. Slater, and J. C. Roberts. Training Interpreters using Virtual Worlds. *Trans Computational Science XVIII*, 7848, May 2013.

[16] P. D. Ritsos, J. W. Mearman, A. Vande Moere, and J. C. Roberts. Sewn with Ariadne's Thread - Visualizations for Wearable and Ubiquitous Computing. In *Workshop, Death of the Desktop Workshop, IEEE VIS 2014, Paris, France*, November 2014.

[17] P. D. Ritsos and J. C. Roberts. Towards more Visual Analytics in Learning Analytics. In M. Pohl and J. Roberts, editors, *EuroVis Workshop on Visual Analytics*. The Eurographics Association, 2014.

[18] J. C. Roberts, C. Headleand, and P. D. Ritsos. Sketching designs using the five design-sheet methodology. *IEEE Transactions on Visualization and Computer Graphics*, 2015.

[19] J. C. Roberts, P. D. Ritsos, S. K. Badam, D. Brodbeck, J. Kennedy, and N. Elmqvist. Visualization beyond the desktop–the next big thing. *CG&A, IEEE*, 34(6):26–34, Nov 2014.

[20] K. Robinson. *Finding your element: How to discover your talents and passions and transform your life*. Penguin UK, 2013.

[21] C. Romero and S. Ventura. Educational data mining: a review of the state of the art. *Trans. SMC, Part C: App and Rev.*, 40(6):601–618, 2010.

[22] A. Ryan and D. Tilbury. Flexible pedagogies: new pedagogical ideas. *Higher Education Academy, London*, 2013.

[23] J. L. Santos, S. Govaerts, K. Verbert, and E. Duval. Goal-oriented visualizations of activity tracking: a case study with engineering students. In *Proc. Learning Analytics and Knowledge*, pages 143–152. ACM, 2012.

[24] M. Swan. Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0. *JSAN*, 1(3):217–253, 2012.

[25] M. Swan. The quantified self: Fundamental disruption in big data science and biological discovery. *Big Data*, 1(2):85–99, 2013.

[26] K. Verbert, H. Drachsler, N. Manouselis, M. Wolpers, R. Vuorikari, and E. Duval. Dataset-driven research for improving recommender systems for learning. In *Proc Learning Analytics and Knowledge*, pages 44–53. ACM, 2011.

[27] K. Verbert, E. Duval, J. Klerkx, S. Govaerts, and J. L. Santos. Learning analytics dashboard applications. *American Behavioral Scientist*, page 0002764213479363, 2013.

[28] M. Weiser. Some computer science issues in ubiquitous computing. *Commun. ACM*, 36(7):75–84, July 1993.

[29] L. Yuan, S. Powell, and J. CETIS. Moocs and open education: Implications for higher education. JISC CETIS, WP01.